Essays in Applied Microeconomics

By

Chengzhen Fang

Submitted to the Department of Economics and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Chair: David Slusky

Donna Ginther

Tsvetan Tsvetanov

Jo Lugovskyy

John Kennedy

Date Defended: May 8, 2023

The dissertation committee for Chengzhen Fang certifies that this is the approved version of the following dissertation:

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Abstract

This dissertation has three chapters. In the first two chapters, I have studied the left-behind children issue in China. According to the latest statistics (2018 Ministry of Civil Affairs), there are 69.7 million children who are separated from their migrant worker parents and are receiving education in their respective hometowns which accounts for more than one-fifth of the Chinese children population today. Hence, there is significant amount of literature on this. However, in the process of studying the causal effect of left-behind children's status on the outcome variables, endogeneity has always been a challenge. My contribution in the literature is the deployment of two stage least square method to reduce endogeneity. I have used the family Hukou type of left-behind children as an instrumental variable in order to analyze the outcome variable, which is a novel attempt with more technical robustness. In the third chapter, we focus on the widely known "Hot Hand" phenomenon in the NBA. The "Hot Hand" phenomenon is the perception that whenever a player starts to make consecutive shots, he/she is more likely to continue making those shots for being on a "hot streak". In our research, we focused on the impact of an NBA player's first shot in a game on the behavior of subsequent players, coaches, and opposing players. Since the first shot in a game represents a player's first impression which is of paramount importance, we believe that previous researchers have not given its necessary attention. Our research also sheds light on the importance of the phenomenon of first impressions in everyday life.

Acknowledgements

I would like to express my gratitude to my advisor Professor David Slusky for his guidance, support, and patience throughout the process. His expert comments and directions were immensely valuable for this thesis. I strongly believe that the knowledge I have garnered from him will guide me in my future endeavors beyond KU.

I would also like to thank my thesis committee member Professor Donna Ginther, Professor Tsvetan Tsvetanov, Professor Jo Lugovskyy, and Professor John Kennedy (external) for their valuable comments and suggestions. Moreover, I would like to thank the Department of Economics at KU for giving me the opportunity to explore this research horizon.

A heartful gratitude to my parents for their unconditional blessings and love. I dedicate this thesis to my grandparents for always believing in me.

Contents

Chapter 1: The Academic Performance of Left-behind Children

Abstract:

There are 69.7 million left-behind children in China. A lot of parents in China migrate for work and hence they are separated from their children due to policy and economic factors. This results in what we recognize as "left-behind" children. The left-behind children grow up and receive education without their parents. The absence of parents makes them always struggle and feel helpless during their growth. I will use administration student-level data from a county-level education department in China to examine the differences between left-behind children's academic performance with other children of the same cohort. It is found that left-behind children earn 1.474 standard deviations (SDs) less total scores than their peers from the county-level exam.

1 Introduction:

In the past three decades, China has experienced rapid development and urbanization. Due to a rural-urban wage gap, we have seen millions of laborers leaving rural areas to work in urban areas and thus the labor force has been redistributed simultaneously (Lewis model 1953; Basu 1997). The main labor exporting provinces are mainly located in central China, including Henan, Anhui, Shanxi, etc, and the main labor importing provinces are located in the more developed southeast area areas including Guangzhou, Shanghai, Zhejiang, etc (National Bureau of Statistics 2019). According to the National Bureau of Statistics of China, the population of migrant workers in 2019 was 297.77 million and by Du (2000) this number was only 37 million in 1994. So, the size of migrant workers population has increased by 9 times in last the 25 years, which is the largest human migration in human history.

Migrant workers greatly contribute to China's economy. Even though most migrant workers are not endowed with high-skill (Li 2008), because of the complementarity nature of the production process, if workers with a low skill migrate to an area where others have a higher skill, then his productivity will be higher even though his very own skill remains unchanged (Skill-clustering Theorem- Basu 1997; Kremer 1993).

However, due to the limitations of the household registration (*Hukou*) system, if the migrant workers are not registered for that area, they are not eligible to receive social services provided by the local government including education, medical care, and insurance (Chen 2018). At the same time, primary education is mainly operated by the government, which means migrant workers' children will have a hard time receiving the education if they are not registered for that area. Even if they get to receive the education (Self-study or private institution), they are still not eligible to take the entrance exams for the next level of education (Fu and Ren 2010). So, we can see that many parents choose to separate from their children and let them receive education in their hometowns.

According to the latest statistics (2018 Ministry of Civil Affairs), there are 69.7 million children are separated from their migrant worker parents and receiving education in their hometown which accounts for more than one-fifth of the Chinese children population today (All-China Women's Federation 2013). They are called left-behind children and their well-being has become a social issue that cannot be ignored.

I worked with a Chinese local county-level Education Research department directly under the government to analyze the academic achievements of left-behind children through the student-level administrative data they provided. The targeted county Queshan located in Henan province, is one of the main labor export provinces. It has more than 36.8 million migrant workers (China news 2020) and 6.1 million left-behind children (The Collective 2018). My research has two objectives: (1) improving the quality of educational service provided by the county-level education department; and (2) helping left-behind children issue to be known by more people.

Since my research interest is to understand whether the left-behind children status will influence the student's academic performance, I then set my research hypothesis to be: Left-behind children perform worse than their peers in academics.

The data do support my hypothesis, it is found that left-behind children receive1.474 standard deviations (SDs) less total scores than their peers from the county level exam. My contribution is, I am able to get administration student level data (Test result of the unified county-level exams) given its scarcity and study the phenomenon of left-behind children in order to reflect the real academic performance of students.

2 Background and Literature Review:

In this section, I will discuss the background information, including (A) what household registration (*Hukou*) is and (B) why it still exists, and (C) parent's pivotal role in children's growth (D) previous literature about left-behind children's well-being to see this concept more broadly.

2.1 Hukou:

The household registration (*Hukou*) is an old population management and control system. When China was a completely planned economy, *Hukou* primarily served as a demographic database (2009 Chan). Since each state needs to predict how much to produce and what is the expected consumption base on the population they have (Cheng and Mark 1994), *Hukou* served as a very important source of information. The erstwhile system completely prevented population movement where people were forced to stay where they were born. But now with the development of the economy formation, *Hukou* no longer prevents the movement of Chinese people. However, it still controls and restricts the provision of social services (2009 Chan). Local *Hukou* rights make the holder eligible to receive education, health care, land contracts, and housing. When internal immigrants especially migrant workers leave their permanent residence, they are not eligible for these social services unless they transfer their registration to the new area, which has significant operation challenges (2009 Chan; 2016 Tyner & Ren; Mallee 1995).

Therefore, *Hukou* status is an indicator of an individual's social status. Due to quotas and restrictions on *Hukou* transfer, hundreds of millions of immigrants especially migrant workers have been transferred but their *Hukou* cannot go with them, which means they will no longer be able to obtain social services (2009 Chan; 2016 Tyner & Ren.). Since migrant workers are left-behind children's parents, the existence of *Hukou* system closely related to whether or not children are left-behind.

2.2 Why China keeps the Hukou System:

Since China is not a planned economy anymore, you may want to ask why China still keeps this old system which was originally designed for a planned economy. The reason is, due to the unbalanced economic growth in China, the *Hukou* policy is playing some new roles.

Most parts of China are still poor (i.e GDP per capita for Henan province is 56388 Yuan / 8292 USD), but some states (i.e GDP per capita for Beijing and Shanghai are 164220 Yuan /24150 USD and 157297 Yuan/23131 USD) already have a relatively high level of economic growth (National Bureau of Statistics 2020). The growth strategy the government follows is called "Let some states get rich first and then drive other states" (Says Deng Xiaoping). This is in accordance with the unbalanced growth theory by Hirschman. In unbalanced growth theory, it is believed that in order to bring an underdeveloped economy out from a poverty trap, or a “low-level” equilibrium trap, putting a large investment in one sector generates, through "linkages" the scope for expansion in other sectors and finally there takes place a trickle-down effect of growth (Basu 1997). The Chinese government has provided growth generating policies, including taxation, land usage, and resource allocation to some selected states only (Zeng 2012) and the social welfare and development level of those states are far superior to other places (Chen 2018).

In China, one important reason for keeping *Hukou* is reliance on the *Hukou* system minimizes the operation and transactional cost, i.e.; the local government can avoid chaos and overwhelm of their social service system by restricting overwhelmed migrants from other areas to settle and then receive social service at their local area (Chen 2018). For example, in China, we have a Compulsory Education Law which guarantees children to be able to receive a certain level of education. From the law’s Chapter one article two “***The State adopts a system of 9-year compulsory education”***, we get to know: “... Compulsory education is education which is implemented uniformly by the State and shall be received by all school-age children and adolescents. It is a public welfare cause that shall be guaranteed by the State. No tuition or miscellaneous fee may be charged in the implementation of compulsory education. The State shall establish a guarantee mechanism for operating funds for compulsory education ...”. (Compulsory Education Law of the

People's Republic of China 1986). Just like the law stated, the state government needs to guarantee welfare to state residents. Due to budget constraints, if many immigrants suddenly add to the social service system, it will certainly crash like Chen (2018) stated.

To sum up, the reliance on unbalanced growth and lack of social resources like education and medical caused this system to exist in China. Because the *Hukou* is not a simple problem to resolve, left-behind children is a persistent problem as well.

2.3 **Children and Parents:**

There is no doubt that in addition to learning in school, parents also play an important role in children's learning and cognition (Kathleen and Howard 1997).

We know parents' education (Ganzach 2000), income (Khanam, R and Nghiem, S 2016), and marital status (Liu 2012) will affect children's cognitive abilities and learning abilities. Even the parent's character (W.Roger 2015) and educational expectations for the children (Ganzach 2000) exerts a significant impact on children.

However, from Figure 1, we learned that a large proportion of left-behind children can only see their parents once a year during the spring festival. We know for most cases children with migrant worker parents are better off financially (Asis 2006). But still, we can tell the responsibility of being a parent more than fulfilling their offspring's nutritional and material needs. From the next section left-behind Children Literature, we can see those left-behind children are worse off in all-round compared to others in their cohort.

2.4 **Previous Literature:**

In recent years, more and more research on left-behind children has been released to the public. We know that left-behind children are more likely to have psychological problems (Fan, Su 2009; Su 2012), such as they are more anxious (Zhao 2014; Dai and Chu 2018), at a higher risk of depression (He 2012), and more likely to have a suicidal idea (Cottledge 2015; Dunifon 2014).

Studies also tell us that left-behind children have worse physical development and nutritional status than their peers (Zhou 2015), they tend to have a slower height growth and weight gain than their peers (Zhang, Becares, & Chandola 2015). At the same time, we also know that the performance of left-behind children in school is worse than non-left-behind children (2015 Zhou; Dai and Chu 2018).

What is even more concerning is that in an official survey in 2017 (2017 State Council Information office), 10% of left-behind children told visitors that their parents had died already. But in fact, they were still alive, this shows the psychotic disorder of some of these children (2017 State Council Information office). Thus, the unfortunate thing we can also see is, left-behind children and adults have a higher chance of getting involved into illegal activities. We know they have a higher chance of sexual harassment others and have a higher chance of being sexually harassed (Lau 2013; Whiteman 2012), they also more likely to have risky/delinquent behaviors (Chen 2009), like violent abuse.

3 Data sources and elements:

I use student-level data from my hometown county Henan, Queshan for my analysis. This county has a single ethnic group and the resident income gap is small and thus we are able to better focus on the causality aspect of the problem. Also, this county located in the central region of China is a typical representative of a labor export county. I will select information from the following two secondary data sets to build my own data set for analysis work.

The first part of data sources is the unified county-level test scores (2019 fall) among the county's middle schools conducted by the education department of Queshan County. This unified examination takes place twice a year and contains two parts: mathematics and verbal. The data contains information which includes math and verbal scores, inter-county rankings, student ID, and school name. The aggregated score is my dependent variable and I will also use the student ID to merge the second part of primary data which is the personal information of students from each school to get the final data for analysis.

The second part of the data source is basic information about students. This part of the information is recorded and stored by each school, including student age, gender, left-behind children status, number of siblings, and whether this student receiving financial help from the government. The summary statistics for this data set is provided as table 1 and 2.

4 Empirical Work:

My identification strategy is twofold. To examine the nature of the direct causation in the Left-behind Children Statues - student achievement relationship, I started with estimating the following linear model.

$$T_i = X'_i \beta + \alpha L_i + F + \varepsilon_i \quad (1)$$

Where the index i indicates the individual.

★ T is the test score for the unified exam.

- ★ X is a vector of controls, including gender, number of siblings, whether receiving financial assistant from government, *Hukou* type, age
- ★ L is a binary variable equal to 1 if this student is a left-behind child, 0 otherwise.
- ★ F is a fixed effect term, including school fixed effect, cohort fixed effect.

To account for the omitted variable bias problem caused by unobserved student-level characteristics which, in turn, is correlated with left-behind children status and student academic achievement. We estimate 2SLS models and instrument for Left-behind children status with their family *Hukou* type. In literature, *Hukou* type is a widely used instrument variable: Song, and Zhu (2011) had used *Hukou* type as an instrumental variable for the employer's employment decisions to study the labor force participation rate. Liao and Zhang (2020) use mother's *Hukou* type as an instrumental variable for children's *Hukou* status to study market housing demand. Tse (2016) uses the proportion of urban *Hukou* as an instrumental variable in order to capture the prejudice towards rural migrants to study employers' biasness towards rural population, etc. In order to know why *Hukou* is a valid instrument variable for Left-behind children status, now we need to discuss how it works for our sample group.

Since we know, once someone leaves the geographical location they registered, they will be treated differently from local residents and hence, they lose the ability to receive certain social services. In particular, two individuals registered for the same geographical location, they maybe have different *Hukou* type and enjoy different rights.

There are two types of Hukou: agricultural (rural) Hukou and non-agricultural (urban) Hukou. Rural Hukou are usually assigned to residents who live in villages; urban Hukou are usually for those who live in towns and cities. Each type of Hukou enjoys different and specific rights. With respect to rights and entitlements, those holding rural Hukou are distributed arable land for their livelihood while urban Hukou holders have access to government jobs, subsidized housing, education, and healthcare. (China Briefing 2019)

Because of the difference between urban Hukou holders and rural Hukou, We see urban holders have a higher change to get a tenured job (Chun 2016) with a high propensity to get a minimum subsistence, layoff subsidies, and unemployment insurance (Hussain 2003, Mukhopadhyay, Song and Zhu 2011) and they also have a lower chance to become a migrant worker (Liao and Zhang 2020). Thus, we are able to make the assumption, there is a direct correlation between someone's Hukou type and whether this individual becomes a migrant work. Meanwhile, by assuming family Hukou type will not directly influence children academic performance in the school -- which school the children can get in is influenced by their family Hukou type. But once children already study in the same school, it is reasonable to assume the Hukou type will not influence their academic performance. By making those two assumptions, we can then apply family Hukou type as IV for left-behind children status to understand how left-behind status influences children's academic performance.

Then the **first stage regression equation** is designed to be:

$L_i = X'_i \delta + \gamma Z_i + \theta_i$

★ Z is the indicate variable for children's family Hukou type.

★ X is a vector of controls including gender, number of siblings, whether receiving finical assistant from government, age.

★ L is a binary variable equal to 1 if this student is a left-behind child, 0 otherwise.

Once I get the estimator of L_i from the first stage regression which is $Ł_i$, I am able to conduct the second stage regression showing below: T is the test score for the unified exam.

$$T_i = X'_i,\beta + \alpha Ł_i + \varepsilon_i \qquad (2)$$

- ★ T is the test score for the unified exam.
- ★ X is a vector of controls including gender, number of siblings, whether receiving finical assistant from government, age.
- ★ Ł is the estimator we get from the first-stage equation.

5 Result:

Table-3: OLS approach

Firstly, we did not add control variables and fixed effect terms into the model. We directly regress student achievement against left-behind children status which tells us the direct causation between student achievement and left-behind children status. The estimation result is recorded in the first column, which tells us that left behind children get 0.22 SD less total scores than non-left-behind children. The result is consistent with the results we observed from Table-2 which compares the score distribution of left-behind children to non-left-behind children.

Secondly, in order to reduce endogeneity and avoid identification problems, we add our control variables. The estimation result is recorded in the second column. We can see that our estimation tells us that left-behind children get 0.151 SD less than non-left-behind children in the exam, which is lower than our previous result. This may because of fact that our independent variable is correlated with our control variables. Meanwhile, it also coincides with we observed from Table-2.

To control endogenous changes over school and age, we further added age fixed effect and school fixed effect in the estimation which we used to produce column 2. This new estimation's result is recorded in the third column. Our estimation tells us that the gap between left-behind children and non-left-behind children is no longer significant. This is different from what we got before, and it is not consistent with what we observed from the graph either. The possible reason might be, the model still has too much endogeneity, which cause our estimation not accurate.

Table-4 IV approach

In order to improve our estimation, I have used the IV model to further reduce endogeneity. Since the first-stage F-statistic is equal to 98.54 which is above the threshold 10, our instrument variable *Hukou* is not a weak instrument.

To see the direct causation, we also started the analysis with no control variables and fixed effect terms. We only included academic performance as the dependent variable, left-behind children's status as the independent variable, and Hukou as instrument variable in the model. The estimation is included in column 1, which tells us that left-behind children will score 1.463 SD less than non-left-behind children in the exam. This is consistent with our observation from Table2.

Further I added control variables into it to reduce endogeneity and avoid identification problems. The estimation result included in column 2 tells us that left-behind children will get 1.631 SD less than non-left-behind children in the test. This is pretty close to our estimation from column 1 given that the standard deviation is quite big (0.238) and consistent with our observation from Table-2.

Based on the model provided us column 2, I further added the age fixed effect and school fixed effect to the third estimation. We see that left-behind children get 1.474 SD less in the exam than non-left-behind children. This conforms with the previous result and Table-2.

Thus, our estimations from IV models do support our hypothesis which is left-behind children are worse off than its peers in terms of academic achievement.

Table-5 Difference between both parents or one parent migrant for work.

Meanwhile, there is some other question is meaningful to discuss. Mostly in a family, if one of the parents choose to migrate to work, then their children will be raised by the other parent. However, if both of them migrate to work, then their children needs to be raised without parents (Ye and Pan 2008). The question is whether there is a difference in terms of academic achievement between being raised by one of the parents or none. In order to answer this question, we have selected out all the left-behind children and change our independent variable to whether both parents migrant for work (dummy variable =1 it means both parents migrate for work, and dummy variable =0 means one of the parents migrant for work) for the following analysis.

We have started with OLS approach. The estimation includes student's academic performance as the dependent variable and whether both parents migrate for work as the independent variable. Also, we have added the age fixed effect and the school fixed effect terms. The estimation result is reported in column one. We can see that there is no significant difference between being raised by one of the parents and the absence of both parents. This is also consistent with our observation from Table-6.

We again apply our IV method for the analysis. We take the student's academic performance as the dependent variable, whether the parents go out to work at the same time is the independent variable, the household registration type as the instrumental variable, plus the school fixed effect. The estimation result is reported in column two. We can see that our estimation still tells us that there is no significant difference between being raised by one of parents or totally absence with parents.

6 Conclusion:

Why left-behind children worse off than its peer in terms of academic performance?

Since left-behind children's parents are not around, and mostly their grandparents have limited ability to protect their grandchildren from potential mental and physical harm, it is difficult for left-behind children to maintain their physical and mental health (Ye and Pan 2008). At the same time, left-behind children often need to afford an extra amount of housework (Chang, Dong, and Macphail 2011). Sometimes they need to take care of their aged grandparents (Kong and Meng 2010; Ye and Pan 2008), which affects greatly their study time. Also, left-behind children cannot be properly guided by their grandparents; they are left alone when they encounter difficulties in learning. Therefore, we always see that left-behind children are usually not as good as their peers in terms of academic performance (2015 Zhou; Dai and Chu 2018). Good thing about left-behind children is, with the development of the economy, China has gradually begun to release *Hukou's* influences. In 2014, the Chinese government has been gradually phasing out the distinction between agricultural and urban *Hukou*. As part of the reform initiative, in 2016, the State Council announced a target of granting urban residency status to 100 million rural migrants by 2020. The target specifies that the number of urban

Hukou holders should increase by one percent each year and reach 45 percent of the total population in 2020 (China Briefing 2019). We could expect in the future, left-behind children phenomenon will slowly disappear in history.

Table-1. Descriptive Statistics

Variable	Obs	Mean	Min	Max
Exam score	2809	353.36	14.5	561.5
Gender	2809	.54	0	1
Age	2808	12.66	11	16
Sibling	2809	2.04	0	6
Hukou type	2809	.22	0	1
Assistant	2808	.08	0	1
Parents out	2802	.57	0	2
Left-behind	2809	.43	0	1
Exam score left-behind	1600	362.59	51.5	561.5
Exam score non-left-behind	1209	341.14	14.5	540
Exam score male	1543	338.50	49	561.5
Exam score female	1266	371.48	14.5	548.5
Exam score urban Hukou	634	379.64	49	548.5
Exam score rural Hukou	2175	345.71	14.5	561.5

Table-2. Score distribution

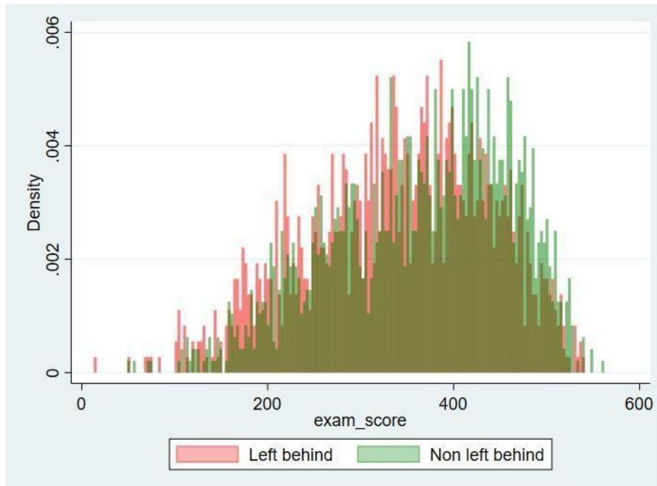

Table-3. OLS approach.

	OLS		
	(1)	(2)	(3)
Left-behind	-0.220***	-0.151***	-0.0478
	(0.0379)	(0.0380)	(0.0383)
Assistant		0.329***	0.342***
		(0.0666)	(0.0618)
Sibling		0.00974	0.0578**
		(0.0296)	(0.0293)
Gender		-0.306***	-0.270***
		(0.0372)	(0.0362)
Hukou type		0.326***	0.209***
		(0.0443)	(0.0445)
Age as control	No	Yes	No
Age fixed effects	No	No	Yes
School fixed effects	No	No	Yes
Cons	0.0948***	2.235***	0.110
	(0.0249)	(0.394)	(0.499)
N	2809	2807	2807

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table-4. IV approach.

	IV		
	(1)	(2)	(3)
Left-behind	-1.463***	-1.631***	-1.474***
	(0.210)	(0.238)	(0.378)
Assistant		0.484***	0.477***
		(0.087)	(0.091)
Sibling		0.0384	0.0654*
		(0.0370)	(0.0345)
Gender		-0.247***	-0.243***
		(0.0469)	(0.0450)
Age as control	No	Yes	No
Age fixed effects	No	No	Yes
School Fixed effects	No	No	Yes
Cons	0.630***	1.770***	1.857***
	(0.0912)	(0.499)	(0.481)
N	2807	2807	2807

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table-5 (Appendix). Difference between both parents or one parent migrant for work.

	OLS	IV
	(1)	(2)
Parent	-0.00310	-2.702
	(0.0577)	(1.646)
Assistant	0.269***	0.144
	(0.0835)	(0.157)
Sibling	0.0349	0.0139
	(0.0444)	(0.0725)
Gender	-0.310***	-0.272**
	(0.0566)	(0.108)
Hukou as control	No	No
Hukou as IV	No	Yes
Age fixed efftcts	Yes	No
School fixed effects	Yes	Yes
Cons	369.2***	769.8
	(13.67)	(907.6)
N	1207	1207

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table-6 (Appendix). Difference between both parents or one parent migrant for work.

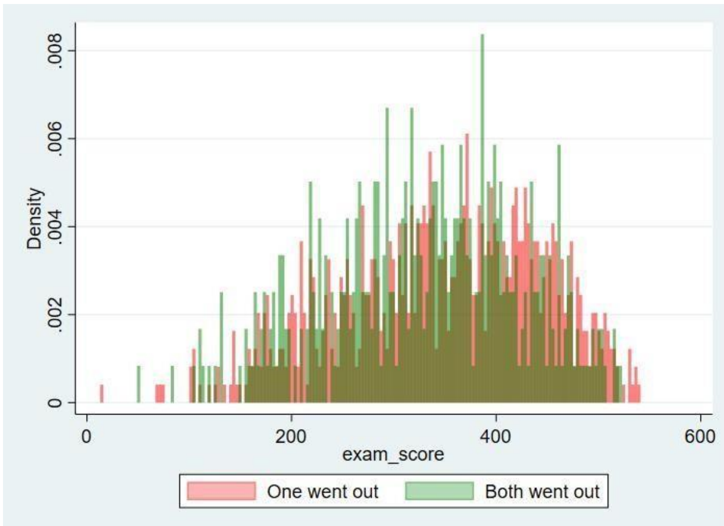

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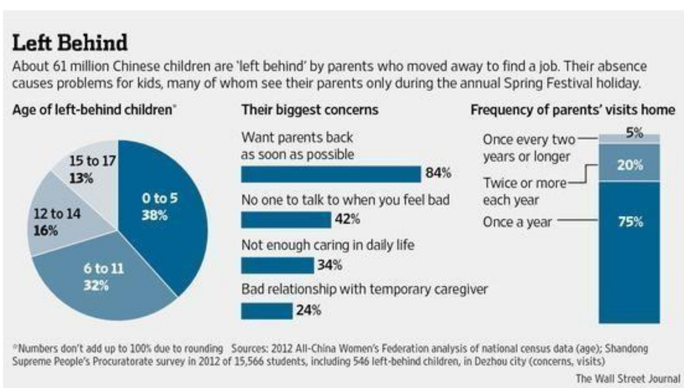
Figure-1



Source: 61 Million Chinese Kids Haven't Seen One or Both Parents for at Least Three Months, 2014.

Table 7 (Appendix) First stage regression result.

	Left-behind
Hukou	-0.210***
	(0.0133)
Gender	0.0296***
	(0.0111)
FE	Yes
Controls	Yes
Cons	-0.00753
	(0.199)
N	2807

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Chapter 2: The Health status of Left-behind Children

Abstract:

Because of the physical absence of parents, left-behind children's conditions have been observed to deteriorate from various dimensions. One of the most important aspects in this regard is the physical health status of the children. I have used their Hukou type as an instrumental variable (IV) on their Left-behind children's status and find the causal effect of Left-behind children's status on children's height and weight. My analysis finds that Left-behind boys are shorter and lighter than their counterparts, the impact on girls are not significant for both height and weight.

1 Background

China has achieved 8 percent average annual GDP growth in the past forty years and this has helped the China to get rid of extreme poverty, and per capita GDP has reached $10,000 per annum (Figure 1). Since China has mostly followed the path of unbalanced growth (more details in Chapter 1), growth generating policies (by the government) including taxation, land usage, and resource allocation has been exercised to some selected states only (Zeng 2012) and this leads to a huge gap in wage levels across regions. Thus, development level of each state in China is different from each other. Consequently, many workers immigrated to the coastal states to work.

However, because of the restriction of the household registration (Hukou) system, people's welfare was tied to their place of residence. Hence parents are often separated from their children and it has been generally observed that those left-behind children receive education in their respective hometowns (More details in Chapter 1). Because of the physical absence of parents, Left-behind children's conditions have been observed to deteriorate from various dimensions. It is well-know that the left-behind children are more likely to have psychological problems (Fan, Zhao, and Chen 2014) and susceptible to acquire risky/delinquent behaviors (Chen 2009). It has also been observed that the performance of left-behind children in school is worse than non-left-behind children (2015 Zhou; Dai and Chu 2018). One of the most important aspects in this regard is the aspect of physical health status of those children. In the existing literature, there are two separate views on this. One school of thought is that rising family income improves children's nutrition, health costs, and living conditions (Wang, elt 2014). However, other studies have found that the left-behind children consume more fat and less protein compared to their counterparts, which in turn results in obesity and acts as a hindrance to physical growth (Zhang, et 2015). A recent study (Zhao, 2018) also portrays a pessimistic picture on this matter since the left-behind children have lighter weight, less height despite being older to the other children in their cohort. The primary motivation of this chapter is to throw light on this dichotomy and providing a categorical answer on the aspect of the physical health of the left-behind children .

The approach here is using left-behind children's status as an instrumental variable (IV) on their family Hukou type and then finding the causal effect of left-behind children's status on children's height and weight. The analysis finds that left-behind boys are shorter and lighter than their counterparts. Interestingly the impact on girls are not significant from both height and weight perspective.

2 Data sources and elements[1]

[1] Since this is the same data set used on the first chapter, please refer to the first chapter for a more in-depth explanation.

The source of the data is from the counties of Henan, Queshan which is located in the central region of China and is a typical representative of a labor export county. The analysis is also supported by the secondary data set which contains the following information at the school level: students' age, gender, left-behind children status, number of siblings, whether this student is receiving financial help from the government and some other relevant information. This can be summarized in the following table as:

3 Empirical work

To examine the direct causation in the Left-behind Children Status - student health status, the following linear model is estimated

$$H_i = X'_i \beta + \alpha L_i + F + \varepsilon_i \qquad (1)$$

Here the index i indicates the individual.

- ★ H are outcome variables including height and weight.
- ★ X is a vector of controls, including gender, the number of siblings, whether receiving financial assistance from the government, *Hukou* type, age, parents' height, and family income.
- ★ L is a binary variable equal to 1 if this student is a left-behind child, 0 otherwise.
- ★ F is a fixed effect term, including school fixed effect, and cohort fixed effect.

At the same time, by assuming family Hukou type will not directly influence children height and weight; there is a direct correlation between someone's family Hukou type and whether this individual becomes a migrant worker. We have applied family Hukou type as IV for left-behind children status to find the causal effect of Left-behind children's status on children's height and weight. Then the first stage regression equation is designed to be:

$$L_i = X'_i \delta + \gamma Z_i + \theta_i \qquad (2)$$

- ★ Z is the indicator variable for children's family Hukou type.
- ★ X is a vector of controls including gender, the number of siblings, whether receiving finical assistance from the government, age, parents' height, and family income.
- ★ L is a binary variable equal to 1 if this student is a left-behind child, 0 otherwise.

Once I get the estimator of Li from the first stage regression which is Łi, the following second stage regression has been exercised:

$$H_i = X'_{i},\beta + \alpha Ł_i + \varepsilon_i \qquad (3)$$

- ★ H are outcome variables including height and weight.
- ★ X is a vector of controls including gender, the number of siblings, whether receiving finical assistance from the government, age, parents' height, and family income.

- ★ Ł is the estimator we get from the first-stage equation.

4 Result

Table 2 shows the regression result for children's height. Column (1)-(3) shows the result of our OLS approach for girls' group, boys' group and pooled group separately. Column (1) is for girls' group only, whether their parent immigrant for work has no significant impact on their height. Column (2) is boys' group, where left-behind boys are 0.86 centimeters shorter than its counterparts with a standard deviation 0.402. Column (4) - (6) shows the regression result from our IV approach, from column (4) we again see that for girls whether their parent's immigrant for work has no significant impact on their height. Column (5) is for boys' group, where left-behind boys are 8.001 center meters shorter than its counterparts with a standardization 2.044.

Table 3 show the result for children's weight. Column (1) - (3) are the OLS regression results. From column (1) we see their parents immigrant for work or not has no significant impact on girl's weight. Column (2) shows the result for boys' group, as we can see left-behind boys are 2.714 Chinese pound (1.357 Kg) lighter than its counter parts with a 1.192 standard deviation. Column (4) – (6) includes the regression result from our IV approach. from column (4) we conclude that for girls whether their parent's immigrant for work has no significant impact on their weight. From column (5) we find that left-behind boys are 23.35 Chinese pound lighter (11.675 KG) with a standardization 6.281.

The question is why the absence of parents has a significant effect on the height and weight of boys but not on the height and weight of girls? In order to understand this problem, we need to understand the growth curves of boys and girls first. As shown in Figure 2, the growth peak of girls is between 11 and 13 years old. And the growth peak of boys starts from 12 to 15 years old. From our sample we know that the average age of the children is 12.66 years old, with a standard deviation 0.57. The actual average age of the children should be higher than 12.66 years old, because in the original data, the age appears in the form of a whole year, such as 13 years old, rather than in the form of years plus months, such as 13 years and 4 months. Therefore, we can reasonably predict that the average age of children should be around 13 years old. So we can tell that girls are basically past their growth peaks and boys are just entering their growth peaks from our sample.

At the same time, the jobs of their parents got as a migrant worker are very unstable, they may need to change jobs frequently, or they may be unemployed for a significant duration (Cai 2019). In that case they will back to their hometown to live there to reduce the living cost. Therefore, whether the children's parents in the data are working outside means that the parents are working outside when the data was taken. For girls, since we don't know whether their parents are around them between the ages of 11 and 13 which has the greatest impact on them but for boys, they are in the peak growth period, and we can see that the absence of parents has a huge impact on them.

Is there another possibility? We first need to know more about Chinese society. Chinese society has a very strong son preference. In pre-revolutionary time, if a wife was unable to give birth a son for the family, the husband could use this as a reason divorce his wife (Hillier, S. 1988). Because of China's previous one-child policy where a family could only have one child, we see parents choose not to register girls until a boy was born. Even from the government's policies, we can see the shadow of patriarchy. In the early days of one-child policy villagers could legally have a second child if the firstborn was a girl (Kennedy 2019). Then there is another possible explanation why my analysis has completely different results for boys and girls, that is, girls get very little care and attention even when their parents are around, and their parents' going out will not even affect them much. But boys receive a lot of attentions when their parents are at home, so once their parents go out to work, the situation of boys deteriorated so much.

5 conclusions[2]

In this chapter, I have looked at the impact of the left behind children status as on children's weight and height. From the analysis we can therefore conclude that the presence or absence of parents is crucial for children in their growth peaks, and their absence can have a huge impact on children. Since the government has become more focused on the welfare aspect of its population, the *Hukuo* system has started to undergo significant changes since 2014. The current government's view and changes on the *Hukuo* system can lead to different effects between cohorts

[2] Please refer to chapter 1 for a more in-depth conclusion.

and we may expect younger children to be in a much more favorable position than the older cohorts due to a change in the policy.

Table 1 – Summary stats:

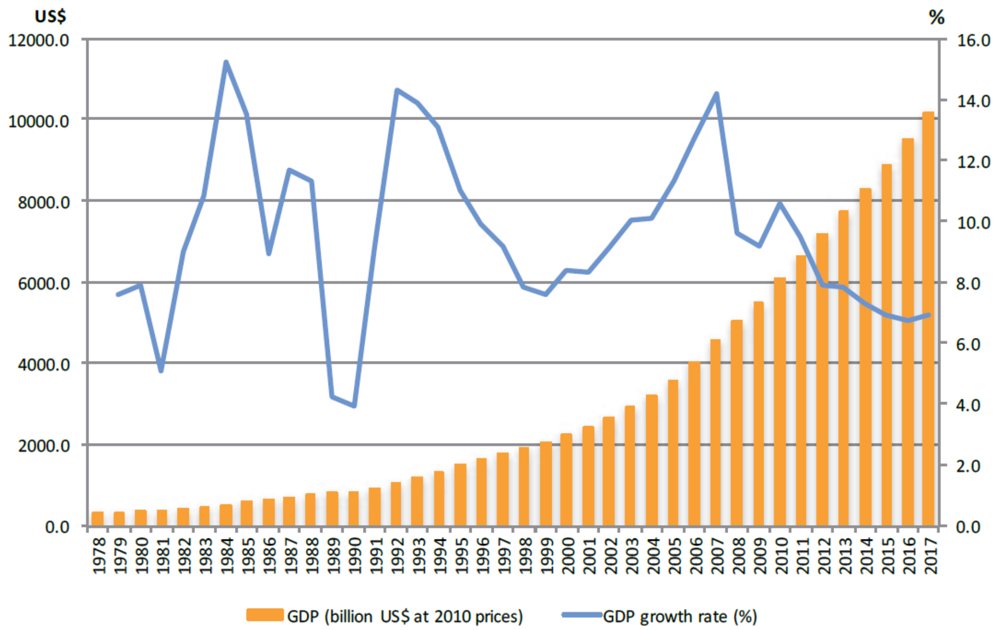
	Obs	Mean	Std.Dev	Min	Max
Gender	2640	0.55	0.50	0	1
Age	2640	12.66	0.57	11	15
Num sibling	2640	2.045	0.65	0	6
Assistant	2640	0.09	0.29	0	1
Weight	2640	99.08	20.36	64	230
Height	2640	163.24	7.25	135	187
Parents out	2640	0.57	0.72	0	2
Mom Height	2640	165.11	31.88	146	189
Father Height	2640	173.97	6.04	153	195
Income	2640	2.54	1.29	1	5
Live with	2640	1.17	0.47	1	3

Table-2: OLS&2SLS *Height*.

	(1) Height	(2) Height	(3) Height	(4) Height	(5) Height	(6) Height
Left behind	-0.311	-0.860**	-0.655**	-1.991	-8.001***	-6.192***
	(0.299)	(0.402)	(0.263)	(2.596)	(2.044)	(1.641)
Sibling	-0.784***	0.0379	-0.374*	-0.679**	0.131	-0.158
	(0.213)	(0.369)	(0.210)	(0.273)	(0.388)	(0.230)
Income	0.0855	0.461***	0.313***	0.0545	0.345**	0.219*
	(0.114)	(0.157)	(0.104)	(0.127)	(0.173)	(0.115)
Mom age	0.0919*	-0.104	0.0000871	0.0960*	-0.167*	-0.0212
	(0.0525)	(0.0866)	(0.0528)	(0.0528)	(0.0954)	(0.0564)
Father age	-0.0326	0.100	0.0217	-0.0466	0.138	0.0164
	(0.0549)	(0.0874)	(0.0546)	(0.0574)	(0.0957)	(0.0578)
Mom height	0.277***	-0.00297	0.0000322	0.276***	0.000464	0.00270
	(0.0328)	(0.00444)	(0.00673)	(0.0325)	(0.00513)	(0.00720)
Father height	0.242***	0.222***	0.251***	0.237***	0.240***	0.251***
	(0.0290)	(0.0478)	(0.0328)	(0.0309)	(0.0469)	(0.0315)
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Female	Male	4.113***	Female	Male	4.317***
			(0.257)			(0.285)
_cons	74.51***	125.1***	115.1***	71.87***	122.3***	115.4***
	(6.774)	(8.889)	(6.074)	(7.973)	(8.758)	(5.896)
N	1188	1452	2640	1188	1452	2640

Table-3: OLS&2SLS *Weight*.

	(1)	(2)	(3)	(4)	(5)	(6)
	Weight	Weight	Weight	Weight	Weight	Weight
Left behind	-0.657	-2.174*	-1.524**	-10.68	-23.35***	-19.58***
	(0.894)	(1.192)	(0.772)	(8.411)	(6.281)	(5.078)
Sibling	-1.452**	-1.015	-1.285**	-0.825	-0.720	-0.572
	(0.580)	(0.905)	(0.519)	(0.806)	(1.016)	(0.609)
Income	-0.148	0.772	0.385	-0.333	0.422	0.0751
	(0.388)	(0.488)	(0.325)	(0.418)	(0.540)	(0.362)
Mom age	0.128	-0.345	-0.112	0.152	-0.530**	-0.180
	(0.174)	(0.243)	(0.150)	(0.173)	(0.270)	(0.161)
Father age	0.0302	0.205	0.105	-0.0534	0.315	0.0867
	(0.175)	(0.236)	(0.150)	(0.188)	(0.257)	(0.160)
Mom height	0.180*	0.00246	0.00429	0.174*	0.0126	0.0130
	(0.0952)	(0.0173)	(0.0179)	(0.0977)	(0.0195)	(0.0198)
Father height	0.187*	0.126	0.165**	0.153	0.182*	0.166**
	(0.0981)	(0.0922)	(0.0681)	(0.106)	(0.0977)	(0.0703)
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Female	Male	8.724***	Female	Male	9.395***
			(0.754)			(0.860)
_cons	53.20**	57.83***	37.96***	83.04***	49.52***	38.81***
	(20.65)	(17.48)	(12.75)	(24.64)	(18.42)	(13.19)
N	1188	1451	2639	1188	1451	2639



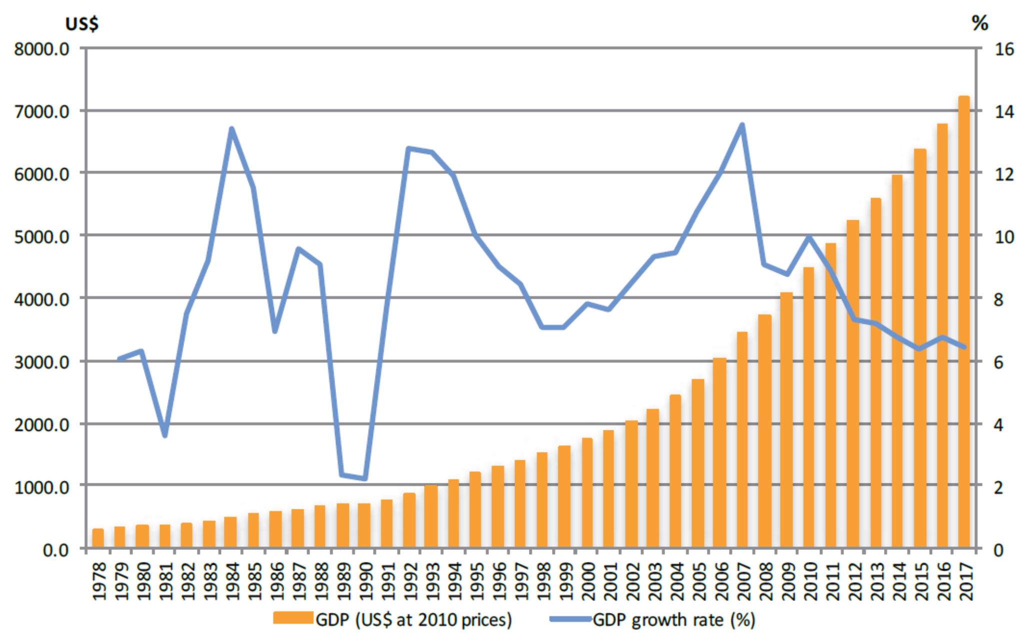


Figure 1 China’s GDP per capita and growth rate, 1978–2017

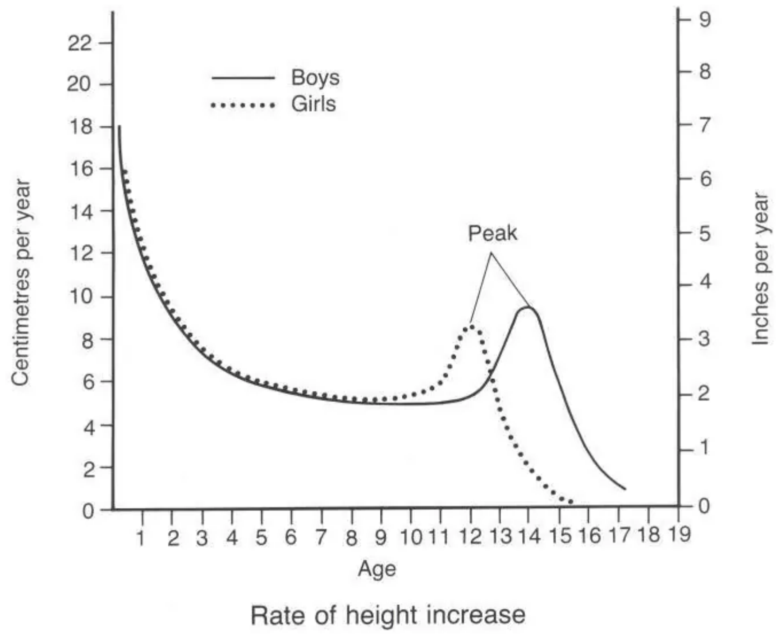


Figure 2: Patterns of Human Growth by Barry Bogin

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Chapter 3 - Give me your best shot: The Impact of NBA Players' First Shot Attempt

Victor Andrade Chengzhen Fang

Abstract:

We attempt to analyze the impact of NBA players' first shot attempt on their overall game performance. Using data from the 10 NBA regular seasons (2011-2021) we find mixed results. Making their first shot of a game leads to the player being on the court 45 to 61 extra seconds. We further confirm the existence of the impact of the first shot by analyzing its impact by half. Successfully hitting the first shot also results in greater overall statistics; but it comes at the cost of being less efficient with the shot selection from the second shot onwards.

1. Introduction

Few sports generate as much discussion about a player's form and momentum as basketball. Since the game is fast paced and ball possession is constantly changing, players regularly find themselves in position to shoot the ball, an action that when successful, results in points in favor of their team. Hence, shooting effectively and scoring points is arguably the most important measurement of the player's impact in the game. Furthermore, instances in which a player scores a tough shot, or scores points two or more times in a row often leads to fans, and commentators to call out a possible hot streak or a "hot-hand." The hot-hand hypothesis is the perception that whenever a player starts to make consecutive shots, he/she is more likely to continue making those shots for being on a "hot streak." Furthermore, consecutive misses will lead to an increase of the likelihood to miss the following shots, a "cold streak." The perception of this hot-hand effect is important because it may change behavior of opposing players who try to defend these "hot" players, coaches who may be more inclined to set up plays for them, and teammates who may also look for the "hot" players as play finishers or security blankets when the opposing team improves their own play. There is a wealth of research discussing the existence or perception of the hot-hand effect starting with Gilovich et al., 1985; which concluded that for those involved in the game (fans, players and coaches), it does indeed exist.

Gilovich et al. 1985's research sparked an interest on the existence of the hot-hand effect in a variety of sports such as golf (Arkes, 2016), soccer (Parsons and Rohde, 2015), volleyball (Raab, et al. 2012) and others. The interest remains strong in basketball where research is divided between controlled environments such as the 3-point tournament, controlled shooting experiments and in-game free-throws (Arkes, 2010; Aharoni & Sarig, 2012; Miller & Sanjurjo, 2014, 2015, 2018;

Yaari & Eisenmann, 2011) which finds evidence in favor of the hot-hand effect. The second area of focus is the run of play scenarios which is focused on field goals being made during the game as a result of the previous shot, and is the shot which the fans, players and analysts might be most interested in (Rao, 2009; Bühren and Krabel, 2015; Csapo and Raab, 2014; Bocskocsky et al., 2014; Lantis and Nesson, 2021); these studies find mixed evidence in favor of the existence of the hot-hand.

This paper aims to apply this hot-hand analysis to a moment in the game that could be just as important as a streak of made or missed shots. We aim to analyze the impact of a player making or missing their first shot in the game. The first shot a player takes in a game could have the potential to be just as impactful as those shot sequences. Basketball is a unique sport because it fields 5 players who despite playing different positions, still all have to attack and defend; meaning that these players have important defensive duties (guarding a specific player or zone) as well as shooting the basketball on the attacking end. We believe that whenever a player starts the game by making his first shot (especially a difficult shot like a contested layup or dunk or a three pointer), it works as a signal that this player will have a good game.

By using play-by-play data as well as the game box score data from every NBA season between 2011 and 2021 we have over 170,000 observations from players who met our minimum requirements (played at least 25 games and averaged 5 Field Goal Attempts (FGA) per game)[3] we can see if the player made or missed his first shot and analyze the impact of this first shot on the

[3] That accounts for the player playing at least a third of the team's games in the majority of the seasons and having significant impact in terms of shooting.

final box score. Our results show that whenever a player makes the first shot, he plays between 45 and 61 more seconds than when he misses his first shot. In a fast-paced game like basketball, this can lead to more shots and even game winning or losing moments.

Our approach aims to answer questions on whether the result of a player's first shot leads to him having an overall better or worse game statistics-wise. Unlike the general hot-hand analysis papers we do believe that the first shot works as a signal to the coach and other players (both teammates and opponents) that the shot-taking player will have a better overall game which may lead to longer playing time and a greater impact in the game. These results could be comparable to Campbell & Thompson (2015) and Bertrand and Mullainathan (2001)'s work on CEO's being rewarded for luck in a sense that this first shot does not significantly impact the game itself and could even be a result of a much better play by another player in either getting a steal/block on the defensive end that leads to a fast-break opportunity or even a timely assist from another player for an easy and open shot.

The rest of the paper is divided in the following sections: 2. Motivation, in which we will discuss previous research and how we decided to do our analysis on the first shot effect; 3. Data, where we will discuss our play-by-play and box score data; 4. Methodology, which consists of our econometric analysis; 5. Results, showing our findings and discussing their relevance; 6. Robustness Checks, where we show that our results hold across different analyses; and 7. Conclusion, which summarizes our findings and suggests next steps and research.

2. Motivation

We look to differentiate ourselves from other hot-hand research by focusing solely on the first shot of the game. We believe that this first shot has the potential to signal what type of game a player is going to have. This means that, this first shot could impact: 1. a player's confidence in himself, 2. Other players, coaches, fans and analysts' perceptions on how well the player is going to play. Economists do not often investigate self-confidence situations due to the difficulty in gathering detailed data from people on their choices and psychological effects; furthermore, it is extremely hard to quantify subjective answers. However, self-confidence has been shown to affect individuals' capacity to accumulate human capital (Filippin and Paccagnella, 2012) and also interact with other individuals (Bénabou and Tirole ,2000).

Thus, it is safe for us to assume that athletes are also subjected to the effects of self-confidence. In fact, much praise is given to Michael Jordan's competitive personality and Kobe Bryant's "mamba mentality" of behaving like there are no better players than them as shown in the Netflix documentary "The Last Dance" and interviews from teammates, opponents and themselves.[4] Feltz (2007) finds evidence that a lack of confidence does indeed harm a player's performance while more confident athletes will have a better result both in individual and team sports, despite needing help from the coach to work as a manager. On the opposing side of the "mamba mentality", during the 2021 playoffs, the Philadelphia 76ers were facing the Atlanta Hawks for a place in the conference finals. The series was very competitive with both teams playing well; and ultimately the series went to the 7th game. Ben Simmons, one of the 76ers most important players missed his first shot (a 2-foot layup) and was noticeably affected for the rest of the game and lacking confidence. In total, he attempted only 4 shots and none of them came during the 4th quarter; the

[4] https://www.youtube.com/watch?v=2EtHt6h_63o; https://www.youtube.com/watch?v=aj7fgZQCe0M&t=12s; https://www.youtube.com/watch?v=LQLnDvVlphA

lack of confidence was so evident that at one point during the last quarter he chose to pass the ball to a teammate instead of attempting a shot on a clear path to the basket which could have been an easy layup or dunk. This game was his last as a member of the 76ers since the franchise chose to trade him to the Brooklyn Nets, a decision likely influenced by his performance during that game.

Simmons' story with the 76ers is directly related to confidence; not only did Simmons lack the confidence in himself, but his teammates also did not trust him. He was questioned by analysts over his shooting mechanics and decision-making ever since he entered the league, and he would rarely attempt 3-point shots due to his lack of confidence which turned him into a one-dimensional player. Moreover, the pressure faced by the 76ers has only increased following the start of "the process[5]" of turning the team around from the worst of the league into title contenders; this pressure certainly affected Simmons negatively. In the post-game interview following the loss, the 76ers head coach Doc Rivers openly said he does not know if Ben Simmons can be the point guard on a championship team.

Furthermore, following the NBA's evolution and focus on 3-point shots since the inception of the 3pt line, we have experienced an increase in the number of 3-point specialists or 3-and-D players. Like the name suggests, these players are known and hired for specializing into one or two mechanics of the game, (long-range shooting and defending). 3-point specialists are good example of players that could have a different game if they are on a "hot" night. Duncan Robinson is a 3-point specialist for the Miami Heat that shows a distinct behavior in games which he starts

[5] The period in which the 76ers went into a rebuilding phase that started when they drafted Joel Embiid who was hurt but always said in interviews "trust the process"

by making his first shot. In games which his first attempt is successful (usually a 3 pointer) he finishes with a field goal percentage (FG%) of 56%, while in games which he misses his first shot, he finishes with a FG% of 36%. Since he averages 10 shots per game, making the first shot leads to 2 more FG scores for the Miami Heat, the equivalent of at least 4 extra points.

Another scenario comes from the 1991 NBA Finals. The Chicago Bulls were fighting for their first championship in franchise history; the team was heavily carried by Michael Jordan and Scottie Pippen but in Game 5, the last of the series, it was John Paxson who hit his first shot of the game (also the Bulls first points of the game) and finished the game shooting 5/5. During the "Last Dance" documentary, Michal Jordan mentions how in the final minutes of the game he gave the ball to Paxson who made the shot following a Bulls timeout, and Jordan says "Alright, let's do it again", and he kept on passing to him since he was having a "hot" night.

3. **Data**

We follow the steps from Lantis & Nesson (2021) and gathered play-by-play data from ten NBA regular seasons[6] from bigdataball[7] The website provided us with detailed events from each game of the season including field-goals, free-throws, fouls, turnovers, and others. The data set provides us with the moment the event took place in the game, who the players were(and their positions) on the court and in the case of shots, it gives us information on the time in the game the

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[6] We do not include the "bubble" games which took place in Orlando during the end of 2019-2020 after it was postponed by 3 months due to the Covid-19 pandemic due to its unique environment and circumstances (season cut short, teams with no playoff aspirations were not invited and no fans in the arena.

[7] www.bigdataball.com

shot took place, the distance to the basket, type of shot (jumpshot, 3-pointer, dunk, layup, fadeway, etc.), whether the shot was a make or miss as well as the cardinal position on the court in x-y coordinates.

Additionally, we use http://www.basketball-reference.com to obtain player characteristics ranging from size, years of experience, weight, position as well as whether the player was traded during the season. We also use R's package "bbr" in order to merge the player information to the play-by-play data from bigdataball and filter the players who match our desired characteristics. We use bbr to find the player's "player code" in basketball-reference so we can gather each player's final stat sheet from each game including information on how many points, minutes, rebounds, whether the player started the game or not, and other key stats.

There were over 1 million plays during every season in our dataset as well as over 500 players who dressed up[8] per season for at least one game during that same season. Upon filtering them, we are left with a number of observations[9] ranging from 13,794 to 19,401 from 252 to 299 players depending on the season. Table 1 summarizes our data set with key statistics and characteristics from each season analyzed.

4. Methodology

4.1. Playing time and Statistics

We follow previous NBA hot-hand research (Lantis & Nesson 2021; Lantis & Nesson 2021; Arkes 2010) in order to conduct our analysis. But instead of focusing on shooting streaks we will

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[8] Players taken to the game and are eligible to play in that game.

[9] We are not interested in all events in the game, just the first shot the game's final box score statistics

be analyzing the players final box-score statistics following their first shot of the game. Our regression for the majority of the player statistics follows the form of the following equation:

$$Y_{i,g} = \mathrm{B}_0 + \mathrm{B}_1 FS_{i,g} + \mathrm{B}_2 H_{i,g} + \mathrm{B}_3 GS_{i,g} + \mathrm{B}_4 PC_i + \mu_{(p,t,pl)_i} + \varepsilon_{i,g} \tag{1}$$

Where the dependent variable $Y_{i,g}$ is change in key statistics (like playing time, points, rebounds, among others) from player i in game g such as playing time, shooting percentage, points, rebounds, assists among others following a player's first shot in a game which is our independent variable $FS_{i,g}$, an indicator equal to 1 if the player made the first shot of the game. We further control for whether the game is played at Home (H), the player is starting the game (GS), and other Player Characteristics (PC) which include the player's age, height, weight, years of experience, salary, and race. Lastly, we include position, team, season and player fixed effects $(\mu_{p,t,pl})$.

4.2. **Shooting Efficiency**

We also conduct an analysis of shooting efficiency in the players' shots after their first attempt. In order to conduct this specific analysis, we do have to focus on the players' games in which they shoot at least two shots. Instead of using the basketball-reference FG% for that game, we manually calculate the shooting percentage, so we do not count the result of the first shot. Hence, we subtract the players' FGA by one (the player's first shot of the game) and subtract his FG made by one as well; by doing this, we are able to calculate only the shooting efficiency from the second shot onwards. For example, player i finishes a game shooting 3/5 (FG/FGA), if his first shot was successful then we will only analyze the shots that happened after the first one which would be of 2/4 for a FG% of 50% and he will have an indicator which he made his first shot. If player i has instead missed his first shot his final stat line from shots 2 through 5 would be 3/4 for a FG% of 75% and he will have an indicator showing that he missed his first shot.

5. **Results**

In this section we will discuss the empirical results of making the first shot. We run equation (1) on several key statistics to see how it impacts the players' game in different ways. From areas in which the player has no control over (playing time), to areas in which his game can be influenced by his own actions or how the other players may adjust their styles to play against him. We run these analyses with and without the control variables and fixed effects in order to best explain the impact of the first shot.

5.1. **Playing time**

We begin our analysis by focusing on how a player's playing time changes following the result of their first shot. Hence, we run equation (1) with seconds played being the dependent variable. Table 2 shows the results of this regression across all 10 seasons[10]. The results are consistent over the years, with a made shot increasing the playing time between 45.48 and 61.33 seconds, an extremely impactful increase when we notice that a team has at most, 24 seconds to run an offensive play. Without controls and fixed effects, the increase in playing time ranges between 46 and 72 seconds, which means that making the first shot gives the player the chance to be on the court for at least one extra possession on offense and defense. In reality, the average possession

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[10] Results per year can be found in the appendix

time per play in the NBA during the 2021 regular season was 14.5 seconds according to stats.inpredictable.com which means that making the first shot yielded around 3 extra possessions per game for the player. This increase can be most likely explained by assuming that the first shot works as a signal to the teams' coaches that the player is going to have a better-than-expected game. Assuming that the coach is a win-maximizer agent, he will play the players which should increase the team's chance of victory by its greatest amount and therefore rely on "hot" players.

Furthermore, due to the many stops like timeouts, quarter breaks as well as halftime; coaches can make the necessary adjustments in order to fix any issues while also trying to disrupt the team's momentum. Hence, it is unusual for a player to continue on "hot" streaks through the entire game. Maintaining the assumption that the coach is a win-maximizer agent, he will likely change his perception on the player and make any changes during these breaks. In order to capture these changes, we will run equation (1) and see how the players' playing time will change following his first shot in the first and second halves.

When we isolate the shots and statistics by half, we see that the first shot of each half does indeed increase the players' playing time. Table 3 shows that whenever the player starts by making his first shot in the first half, it increases his playing time around 14 to 19 seconds, which is around the average possession length in the NBA during the sample years. Table 4 shows that whenever the player makes the first shot in the second half, his playing time in that half increases by 30 to 32 seconds, around double the size of the first half shot. This is highly interesting significantly interesting and follows our win maximizer assumption since the coach would want to keep his "hottest" players on the court when it comes close to the end of the game. Table 5 shows the impact of the first shot on the players' time in the second half; and whenever the player starts the game by making his first shot he does play around 18 to 20 seconds longer in the second half alone, which shows that even after a whole half, the players first shot of the game continues to impact the coach perception. Thus, our results show that even across halves the coach sees the first shot as a persistent signal which could be reinforced by a successful shot in the second half. This reinforces the idea that the first shot possibly indicates that the player will have a better night than average, which could help the team win simply by being on the court.

5.2. Shooting percentage

Our second analysis is on the change of the players shooting efficiency following their first shot. This analysis is the closest to the hot-hand hypothesis we performed. According to the hot-hand hypothesis, whenever the player is “hot” the likelihood of making the next shot increases. We want to capture the impact of making the first shot on his shooting efficiency for the next shot attempts. Table 6 shows our results over the 10 years in our data set.

Out results show that following a successful first shot attempt, shooting efficiency decreases slightly for the remaining shots of the game. The reason behind this could be a regression to the mean, in which the player will attempt to shoot the ball around the same number of times every game and a successful shot does not impact his performance at all. Another reason could be a boost in confidence similar to what Feltz (2007) suggested but it actually encourages the player to take tougher shots[11] which leads to a decrease in efficiency. It could also be due to defensive adjustments made by the opposing team similar to what was suggested by Csapo, and Raab

[11] Farther from the basket or contested shots

(2014)'s in which opposing coaches make changes over the course of the game in order to contain a "hot" player.

5.3 Other Statistics

We also run our analysis on other key statistics for basketball players. Making the first shots leads to the player scoring more points, getting more rebounds, assisting more, stealing more balls and committing more blocks. The impact is as significant in percentage terms as the time, which is possibly the explanation for their impact, could be a result of the two to three extra possessions from the increase in playing time. During two to three extra possessions, a player may take up to two or three shots with the increase in playing time. This fact, allied with the findings from Rao (2009), Bocskocsky et al. (2014) and Lantis and Nesson (2021) that players on hot streaks are more likely to shoot their team's next shot, could be the possible explanation behind this increase in all statistics shown on table 7. The steals increase can also be linked to risky behavior, something that has been shown to impact players negatively on the free agent market (Johnson and Minuci, 2020) and could be attributed to overconfidence.

6. Robustness Checks

6.1 Star Players

Furthermore, we must be aware that some players may behave differently than others. Star player have been shown to impact games attendance and viewership (Humphreys and Johnson, 2020; Hausman and Leonard, 1997) and are also rewarded differently than other players (Johnson and Minuci, 2020). The definition of a star player may vary from playing time, to how vaunted the player was entering the league, to all-star game appearances and other accolades, as well as their salary. Thus, we follow the works from Hamilton (1997), Holmes (2011) and Johnson and Minuci

(2020) and define star players as those that are on the 90th wage quantile. By doing this separation we are able to see the impact of making the first shot on non-star players. This is important because players like Stephen Curry, Lebron James, Luka Doncic, Giannis Antetokounmpo among others will continue to play and shoot with great volume, regardless of whether they made or missed their first attempt, since they are the most popular players not only of their respective teams but also of the entire league.

Moreover, role and bench players are also the ones that experience the greatest impact following a successful first attempt which further increases the hypothesis of defensive adjustments. Star players such as Damian Lillard and Lebron James are likely to be under defensive pressure the majority of the game, with plays design to prevent them from getting open shots, and/or facilitating the game to their teammates with their presence on the court; these defensive adjustments should not change regardless of the success of their first shot since they have proven over the years that they can play under pressure (both physically and psychologically). On the other hand, a player like Doug McDermott, Andrew Wiggins, Tim Hardway Jr. (role players, some starters, some bench players) are more likely see an increase in defensive attention following a successful first shot assuming it does indeed work as a signal to opposing teams as much as it works for their coaches. Table 8 shows the impact of the first shot when we exclude star-players from the data set; the greater overall playing time likely suggests that role-players are benefit most from making their first shot than their star-player counterparts.

6.2 **Blowout Games**

We repeat our analysis while also excluding the blowout games (games decided by over 20 points) since it has the potential to interfere with players and coaches' decision making. In blowout games one of the sides has a significant lead and the opponent is unable to overturn it either due to time constraints, offensive/defensive inefficiency, or simply because the other team is playing better than expected. These results in the remaining game time to become what is called “garbage time”. In “garbage time”, coaches from both sides no longer make significant tactical adjustments for the purpose of winning. Thus, they will instead send players who are not in the normal team rotation onto the game hoping to preserve the team’s core and rotation players both by allowing them to get more rest as well as reducing any injury potential. Our results shown in Table 9 without blowout games are still consistent with our main results. In fact, the playing time improvement is even greater when we remove blowout games which means that the starters and rotation players’ first shots are likely valuable to the coach.

6.3 **Coaches’ Race**

We test the combination of coach and player race in order to see if our results could have been a case of own-race bias similar to what Harris and Berri (2016) showed. In the WNBA coaches do not show own-race bias when it comes to limiting players’ playing time. In fact, non-white coaches favor white players and play them longer. Our results shown in Tables 10 and 11 have mixed results since some years exhibit evidence of same race bias while other years do not. Regardless of the existence of same race biasness, the improvement following a first shot still exists which should support our main results.

7. **Conclusion**

Our paper contributes to the basketball and labor literature by addressing an event often overlooked by researchers, the fact that the first shot has the potential to change the coach’s impressions just like how a person is dressed for an interview, the plan chosen for a first date, the first day in the classroom in a new semester. It has the potential to set the tone for how the game is going to go and even though it is certainly not the only event that matters for a basketball player who can still impact the game by defending, assisting and rebounding; scoring points is indeed what lead his team to victory and making one's first shot is a start in the right direction.

By looking just at the first shot, we differentiate ourselves from the hot hand fallacy literature, although our decision is still directly related to theirs. A streak of consecutive shots that could become consecutive makes or misses always start with a first shot. Our results show that making the first shot does impact the player's game beyond simply adding two or three extra points to his statistics. The first shot has the potential to work as a signal for what type of night the player may have and influence the coach's decision to play him more or less depending on the result of his play. Moreover, 50 additional seconds on the court are the equivalent of at least one more offensive possession and one more defensive possession if both teams run the whole 24-second shot clock, which has the potential to slightly inflate the player's stat sheet. In addition to that, the decrease in shooting efficiency shows us that the first shot also has the potential to work as a signal to opposing players in a way similar to the hot hand fallacy found by Csapo and Raab (2014). These results are further confirmed when we test for the first shot in each half as well as testing for the increase in the player's stat sheet.

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Appendix: Tables

Table 1: Summary Statistics (2012-2021)

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Shooting percent	0.44	0.44	0.45	0.44	0.44	0.45	0.45	0.45	0.45	0.46
	(0.19)	(0,20)	(0.19)	(0.20)	(0.20)	(0.20)	(0,20)	(0.20)	(0.20)	(0.20)
Years of experience	5.26	5.42	5.27	5.62	5.55	5.97	5.38	5.52	5.12	5.08
	(4.13)	(4.16)	(3.78)	(3.84)	(4.03)	(3.96)	(4.07)	(3.88)	(5.65)	(3.87)
Timeplayed (minutes)	27.49	27.37	27.73	26.51	26.61	26.48	26.71	26.18	26.53	26.79
	(8.94)	(9.25)	(8.97)	(8.75)	(8.75)	(8.55)	(8.24)	(8.45)	(8.32)	(8.31)
Average points	11.88	11.88	12.29	11.57	11.98	12.29	12.55	12.63	12.90	13.28
	(7.60)	(7.50)	(7.77)	(7.51)	(7.80)	(8.22)	(7.97)	(8.33)	(8.55)	(8.60)
Players Race	0.78	0.78	0.79	0.78	0.78	0.80	0.81	0.78	0.82	0.79
	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	(0.40)	(0.40)	(0.41)	(0.39)	(0.41)
Average Salary	6.02	5.95	5.86	6.11	6.87	8.86	9.29	9.65	10.08	10.77
	(5.01)	(4.97)	(5.17)	(5.05)	(5.81)	(7.42)	(8.17)	(8.66)	(9.47)	(10.31)
Average Player Age	26.36	26.58	26.40	26.78	26.53	26.52	25.51	26.12	26.10	26.13
	(4.00)	(4.02)	(4.05)	(4.02)	(4.14)	(3.99)	(4.19)	(4.13)	(4.16)	(4.29)
# Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880
# Players	252	261	261	288	272	276	268	299	282	290

Note: 2011-2012 season was shorter due to the league's lockout

Table 2. Effects of Making the First Shot on Total Seconds Played (2012-2021)

	Increased seconds	Increased seconds	Increased seconds
Made shot	61.33***	45.48***	45.51***
	(2.51)	(1.98)	(1.74)
Controls		X	X
Position FE			X
Player & Season FE			X
Team FE			X
#Observations	173,527	173,527	173,527

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 3. First Shot 1st half on 1st half playing time (2012-2021)

	Increased seconds	Increased seconds	Increased seconds
Made shot	19.18***	16.06***	14.93***
	(1.19)	(1.11)	(0.88)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	158,720	158,720	158,720

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4. First Shot 2nd half on 2nd half playing time (2012-2021)

	Increased seconds	Increased seconds	Increased seconds
Made shot	32.52***	30.92***	30.34***
	(1.41)	(1.37)	(1.22)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	158,720	158,720	158,720

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. First Shot 1st half on 2nd half playing time (2012-2021)

	Increased seconds	Increased seconds	Increased seconds
Made shot	20.19***	18.99***	19.01***
	(1.41)	(1.37)	(1.22)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	158,720	158,720	158,720

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Effects of Making the First Shot on Shooting Efficiency (2012-2021)

	Shooting Efficiency	Shooting Efficiency	Shooting Efficiency
Made shot	-1.68*** (0.09)	-1.98*** (0.09)	-2.82*** (0.09)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	147,460	147,460	147,460

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 7. Effects of Making the First Shot on Other Statistics (2012-2021)

	Points excluding first shot	Total Rebounds	Assists	Blocks	Steal
Made shot	0.208*** (0.029)	0.060*** (0.013)	0.074*** (0.009)	0.011*** (0.004)	0.025*** (0.005)
Controls	X	X	X	X	X
Position	X	X	X	X	X
Player & Season FE	X	X	X	X	X
Team FE	X	X	X	X	X
# Observations	173,527	173,527	173,527	173,527	173,527

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 8. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No Stars

	Increased seconds	Increased seconds	Increased seconds
Made shot	62.83*** (2.76)	51.95*** (2.23)	50.81*** (1.98)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	141,281	141,281	141,281

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 9. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No blowout games

	Increased seconds	Increased seconds	Increased seconds
Made shot	64.70*** (2.80)	48.47*** (2.16)	48.44*** (1.88)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	145,801	145,801	145,801

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 10. Effects of Making the First Shot on Total Seconds Played (2012-2021) –Coach and Player Race Match

	Increased seconds	Increased seconds	Increased seconds
Made shot	63.69*** (4.06)	47.15*** (3.22)	46.53*** (2.85)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	66,815	66,815	66,815

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 11. Effects of Making the First Shot on Total Seconds Played (2012-2021) –Coach and Player Race Do Not Match

	Increased seconds	Increased seconds	Increased seconds
Made shot	60.14*** (3.18)	44.41*** (2.50)	44.54*** (2.19)
Controls		X	X
Position			X
Player & Season FE			X
Team FE			X
# Observations	106,712	106,712	106,712

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix A: Playing time results across all seasons

Table A1. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	65.20*** (9.19)	59.37*** (8.35)	48.57*** (8.10)	67.28*** (7.68)	72.60*** (7.77)	63.77*** (7.55)	46.92*** (7.39)	65.76*** (7.31)	61.43*** (8.22)	61.87*** (7.92)
Controls										
Position FE										
Player FE										
Team FE										
#Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880

Standard Errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

Table A2. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	50.20*** (7.29)	42.46*** (6.59)	37.72*** (6.31)	52.09*** (5.91)	46.45*** (6.03)	44.56*** (5.91)	39.33*** (5.86)	46.23*** (5.69)	50.06*** (6.38)	48.95*** (5.99)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										
Team FE										
# Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880

Standard Errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

Table A3. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Controls, FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	47.60*** (6.61)	41.67*** (5.73)	42.77*** (5.62)	51.60*** (5.39)	48.84*** (5.31)	44.65*** (5.08)	41.35*** (5.10)	45.37*** (5.02)	44.72*** (5.42)	44.98*** (5.33)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
#Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4. First Shot 1^{st} half on 1^{st} half playing time (2012-2021)

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	15.91*** (3.43)	14.33*** (2.93)	15.99** (2.88)	17.05*** (2.79)	16.35*** (2.70)	12.38*** (2.56)	12.74*** (2.51)	14.99*** (2.54)	14.32*** (2.73)	16.31*** (2.71)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X

#Observations	12,605	16,216	16,300	17,127	16,862	16,992	16,663	17,641	13,654	14,660

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5. First Shot 2nd half on 2nd half playing time (2012-2021)

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	30.89*** (4.65)	33.65*** (4.08)	34.46*** (3.99)	34.68*** (3.79)	34.90*** (3.72)	30.59*** (3.60)	21.78*** (3.58)	25.76*** (3.56)	30.48*** (3.84)	24.57*** (3.83)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
# Observations	12,605	16,216	16,300	17,127	16,862	16,992	16,663	17,641	13,654	14,660

Note: Standard Errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6. First Shot 1st half on 2nd half playing time (2012-2021)

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	18.57*** (4.64)	12.06*** (4.07)	11.84** * (3.98)	24.21*** (3.78)	22.31*** (3.72)	21.98*** (3.61)	15.05*** (3.57)	17.56*** (3.57)	25.25*** (3.85)	22.77*** (3.83)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
# Observations	12,605	16,216	16,300	17,127	16,862	16,992	16,663	17,641	13,654	14,660

Note: Standard Errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Table B1. Shooting Efficiency After the first shot (2012-2021) – No Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
FG% Change	-3.14***	-2.33***	-1.90***	-1.79***	-2.07***	-2.40***	-1.81***	-1.71***	-1.50***	-1.69***
After 1st shot	(0.31)	(0.27)	(0.27)	(0.28)	(0.27)	(0.27)	(0.27)	(0.26)	(0.30)	(0.29)
Controls										
Position FE										
Player FE										
Team FE										
# Observations	11,655	15,166	15,252	15,811	15,550	15,714	15,535	16,426	12,599	13,752

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B: Shooting Efficiency

Table B3. Shooting Efficiency After the first shot (2012-2021) – Controls and FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
FG% Change	-3.74***	-2.91***	-2.64***	-2.72***	-2.94***	-3.21***	-2.55***	-2.59***	-2.48***	-2.57***
After 1st shot	(0.31)	(0.26)	(0.26)	(0.27)	(0.26)	(0.26)	(0.26)	(0.26)	(0.29)	(0.28)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
# Observations	11,655	15,166	15,252	15,811	15,550	15,714	15,535	16,426	12,599	13,752

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2. Shooting Efficiency After the first shot (2012-2021) – Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
FG% Change	-2.99***	-2.08***	-1.61***	-1.47***	-1.81***	-2.13***	-1.45***	-1.25***	-1.04***	-1.29***
After 1st shot	(0.31)	(0.28)	(0.27)	(0.28)	(0.28)	(0.27)	(0.28)	(0.27)	(0.31)	(0.30)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										
Team FE										
# Observations	11,655	15,166	15,252	15,811	15,550	15,714	15,535	16,426	12,599	13,752

Note: Standard Errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C: Other Statistics

Table C1. Effects of Making the First Shot on Total Rebounds (2012-2021) – No Control, No FE

	Points excluding first shot	Total Rebounds	Assists	Blocks	Steal
Made shot	0.444*** (0.038)	0.364*** (0.017)	0.074*** (0.013)	0.062*** (0.004)	0.003*** (0.005)
Controls					
Position					
Player & Season FE					
Team FE					
# Observations	173,527	173,527	173,527	173,527	173,527

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table C2. Effects of Making the First Shot on Total Rebounds (2012-2021) – Control, No FE

	Points excluding first shot	Total Rebounds	Assists	Blocks	Steal
Made shot	0.249***	0.157***	0.096***	0.031***	0.025***
	(0.034)	(0.014)	(0.011)	(0.004)	(0.005)
Controls	X	X	X	X	X
Position					
Player & Season FE					
Team FE					
# Observations	173,527	173,527	173,527	173,527	173,527

Note: Standard Errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table C3. Effects of Making the First Shot on Other Statistics (2012-2021) – No Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Points excluding first FG	0.300***	0.281***	0.322***	0.324***	0.474***	0.587***	0.374***	0.568***	0.523***	0.575***
	(0.129)	(0.112)	(0.116)	(0.109)	(0.114)	(0.120)	(0.118)	(0.119)	(0.139)	(0.135)
Total Rebounds	0.266***	0.373***	0.308***	0.349***	0.379***	0.370***	0.287***	0.443***	0.449***	0.389***
	(0.061)	(0.054)	(0.055)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.059)	(0.056)
Assist	0.093**	0.094**	-0.008	-0.001	0.101***	0.086***	0.071**	0.076**	0.127***	0.132***
	(0.046)	(0.041)	(0.040)	(0.038)	(0.039)	(0.036)	(0.035)	(0.039)	(0.044)	(0.004)
Blocks	0.030**	0.087***	0.059***	0.054***	0.088***	0.056***	0.039	0.077***	0.073***	0.043***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)	(0.039)	(0.012)	(0.015)	(0.014)
Steals	0.040**	0.023	0.015	0.037**	0.044***	0.026*	0.018	0.009	0.031*	0.030*
	(0.018)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.017)	(0.016)
Controls										
Position FE										
Player FE										
Team FE										
#Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table C4. Effects of Making the First Shot on Other Statistics (2012-2021) – Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Points excluding first FG	0.116	0.130	0.199*	0.187*	0.197**	0.332***	0.244**	0.309***	0.389***	0.354***
	(0.114)	(0.100)	(0.102)	(0.096)	(0.010)	(0.103)	(0.104)	(0.104)	(0.120)	(0.114)
Total Rebounds	0.126**	0.182***	0.110**	0.153**	0.159***	0.151***	0.098**	0.156***	0.233***	0.157***
	(0.050)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)	(0.043)	(0.490)	(0.047)
Assist	0.096**	0.130***	0.035	0.041	0.096***	0.105***	0.071**	0.093***	0.163***	0.137***
	(0.038)	(0.033)	(0.034)	(0.031)	(0.033)	(0.033)	(0.035)	(0.033)	(0.038)	(0.037)
Blocks	0.011	0.054***	0.030**	0.023*	0.054***	0.022*	0.0164	0.035***	0.038***	0.012
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)
Steals	0.040**	0.023	0.021	0.041***	0.036**	0.021	0.021	0.001	0.030*	0.030*
	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.016)	(0.016)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										
Team FE										
#Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table C5. Effects of Making the First Shot on Other Statistics (2012-2021) – Controls, FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Points excluding first FG	0.133	0.145	0.229***	0.259***	0.179**	0.226***	0.220**	0.176**	0.248**	0.242**
	(0.102)	(0.088)	(0.089)	(0.085)	(0.087)	(0.086)	(0.090)	(0.088)	(0.102)	(0.098)
Total Rebounds	0.055	0.105***	0.028	0.042	0.064*	0.061	0.043	0.083**	0.057	0.055
	(0.045)	(0.040)	(0.040)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.042)	(0.041)
Assist	0.083***	0.078***	0.033	0.068***	0.059**	0.077***	0.067**	0.065**	0.108***	0.110***
	(0.031)	(0.028)	(0.028)	(0.026)	(0.027)	(0.027)	(0.028)	(0.027)	(0.031)	(0.031)
Blocks	-0.003	0.030**	-0.006	0.032***	0.006	0.006	0.006	0.022**	0.010	-0.003
	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.012)
Steals	0.0374**	0.0185	0.0161	0.041***	0.037***	0.023	0.018	0.012	0.023	0.029*
	(0.017)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.016)	(0.015)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
#Observations	13,794	17,845	17,808	18,879	18,492	18,616	18,010	19,401	14,802	15,880

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix D: Robustness checks

Table D1. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No Stars, No Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	64.89*** (10.17)	62.60*** (9.30)	50.71*** (8.95)	75.17*** (8.47)	78.94*** (8.58)	60.48*** (8.37)	48.41*** (8.12)	63.46*** (8.33)	65.95*** (8.85)	56.63*** (9.05)
Controls										
Position FE										
Player FE										
Team FE										
#Observations	10,941	13,861	15,082	15,385	15,339	14,540	14,439	16,191	12,591	12,912

Standard Errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D2. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No Stars, Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	57.59*** (8.35)	50.04*** (7.71)	45.29*** (6.94)	59.73*** (6.64)	54.42*** (6.79)	47.01*** (6.95)	44.60*** (6.71)	51.46*** (6.39)	57.82*** (7.13)	55.83*** (6.82)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										
Team FE										

#Observations	10,941	13,861	15,082	15,385	15,339	14,540	14,439	16,191	12,591	12,912

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D3. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No Stars, Controls, FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	53.42*** (7.61)	46.62*** (6.69)	48.24*** (6.21)	56.38*** (6.09)	59.49*** (5.97)	48.07*** (6.07)	48.73*** (5.94)	49.55*** (5.71)	51.53*** (6.15)	49.77*** (6.16)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
#Observations	10,941	13,861	15,082	15,385	15,339	14,540	14,439	16,191	12,591	12,912

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D4. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No Blowout Games, No Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	69.05*** (10.24)	59.80*** (9.30)	49.05*** (8.95)	67.92*** (8.47)	78.76*** (8.58)	70.41*** (8.37)	46.05*** (8.12)	74.58*** (8.33)	65.18*** (9.31)	67.04*** (9.05)
Controls										
Position FE										
Player FE										
Team FE										
#Observations	11,647	15,123	15,169	16,094	15,805	15,700	15,481	15,782	12,207	12,807

Standard Errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D5. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No blowout games, Controls, no FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	56.08*** (7.97)	45.88*** (7.22)	41.12*** (6.81)	53.16*** (6.39)	48.27*** (6.54)	47.49*** (6.41)	39.67*** (6.32)	53.78*** (6.33)	52.69*** (7.04)	51.53*** (6.63)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										
Team FE										
#Observations	11,647	15,123	15,169	16,094	15,805	15,700	15,481	15,782	12,207	12,807

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D6. Effects of Making the First Shot on Total Seconds Played (2012-2021) – No blowout games, Controls, FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	53.21*** (7.15)	44.76*** (6.21)	46.29*** (6.00)	51.99*** (5.77)	49.52*** (5.70)	46.43*** (5.53)	43.04*** (5.53)	50.51*** (5.63)	50.94*** (6.03)	48.77*** (5.93)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
#Observations	11,647	15,123	15,169	16,094	15,805	15,700	15,481	15,768	12,207	12,807

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D7. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Coach/Player Race Match – No Control, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	56.61*** (13.44)	66.00*** (12.20)	49.78*** (12.85)	62.24*** (12.76)	75.78*** (12.62)	64.74*** (12.15)	50.57*** (12.30)	66.22*** (12.13)	73.09*** (15.00)	76.38*** (12.85)
Controls										
Position FE										
Player FE										
Team FE										
#Observations	6,762	8,156	7,721	6,474	6,867	7,353	6,325	6,947	4,471	5,740

Standard Errors in parentheses* p < 0.10, ** p < 0.05, *** p < 0.01

Table D8. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Coach/Player Race Match, Control, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	48.40*** (10.42)	40.69*** (9.57)	34.34*** (9.83)	51.52*** (9.83)	44.90*** (9.85)	45.28*** (9.59)	42.24*** (10.01)	49.73*** (9.51)	65.51*** (11.93)	63.23*** (10.04)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										
Team FE										
#Observations	6,762	8,156	7,721	6,474	6,867	7,353	6,325	6,947	4,471	5,740

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D9. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Coach/Player Race Match, Control, FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	41.47*** (9.60)	39.86*** (8.57)	35.01*** (8.72)	60.15*** (9.06)	47.94*** (8.70)	49.37*** (8.54)	38.86*** (8.88)	47.15*** (8.60)	58.63*** (10.33)	54.81*** (9.18)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
#Observations	6,761	8,156	7,721	6,474	6,867	7,353	6,325	6,947	4,471	5,740

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D10. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Coach/Player Race Don't Match No Controls, No FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	73.73*** (12.54)	53.42*** (11.43)	47.50*** (10.33)	70.11*** (9.61)	70.88*** (9.83)	61.72*** (9.55)	45.89*** (9.23)	65.58*** (9.11)	56.42*** (9.83)	54.83*** (10.03)
Controls										
Position FE										
Player FE										
Team FE										
#Observations	7,033	9,689	10,087	12,405	11,625	11,263	11,685	12,454	10,331	10,140

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D11. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Coach/Player Race Don't Match – Control, no FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	54.11*** (10.17)	43.80*** (9.05)	39.82*** (8.18)	51.11*** (7.39)	47.13*** (7.63)	44.74*** (7.52)	38.53*** (7.22)	43.49*** (7.08)	44.40*** (7.54)	41.49*** (7.44)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE										
Player FE										

Team FE										
#Observations	7,033	9,689	10,087	12,405	11,625	11,263	11,685	12,454	10,331	10,140

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Table D12. Effects of Making the First Shot on Total Seconds Played (2012-2021) – Coach/Player Race Don't Match – Control, FE

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Seconds increase	52.95***	41.39***	48.46***	47.33***	49.28***	41.37***	43.23***	44.63***	38.34***	38.84***
	(9.08)	(7.66)	(7.33)	(6.65)	(6.65)	(6.48)	(6.36)	(6.36)	(6.54)	(6.68)
Controls	X	X	X	X	X	X	X	X	X	X
Position FE	X	X	X	X	X	X	X	X	X	X
Player FE	X	X	X	X	X	X	X	X	X	X
Team FE	X	X	X	X	X	X	X	X	X	X
#Observations	7,033	9,689	10,087	12,405	11,625	11,263	11,685	12,454	10,331	10,140

Standard Errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01